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Short-term quantitative precipitation forecasting using an object-based approach

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SUMMARY

Short-term Quantitative Precipitation Forecasting (SQPF) is critical for flash-flood warning, navigation safety, and many other applications. The current study proposes a new object-based method, named PERCAST (PERsiann-ForeCAST), to identify, track, and nowcast storms. PERCAST predicts the location and rate of rainfall up to 4 h using the most recent storm images to extract storm features, such as advection field and changes in storm intensity and size. PERCAST is coupled with a previously developed precipitation retrieval algorithm called PERSIANN-CCS (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Cloud Classification System) to forecast rainfall rates. Four case studies have been presented to evaluate the performance of the models. While the first two case studies justify the model capabilities in nowcasting single storms, the third and fourth case studies evaluate the proposed model over the contiguous US during the summer of 2010. The results show that, by considering storm Growth and Decay (GD) trends for the prediction, the PERCAST-GD further improves the predictability of convection in terms of verification parameters such as Probability of Detection (POD) and False Alarm Ratio (FAR) up to 15–20%, compared to the comparison algorithms such as PERCAST.

1. Introduction

Short-term Quantitative Precipitation Forecasting (SQPF), or "nowcasting", is important for a number of hydrometeorological applications (Ganguly and Bras, 2003; Afshar et al., 2010). Both Numerical Weather Prediction (NWP) models and extrapolation-based techniques are widely used in SQPF. While these two methods are different in terms of their approaches, they play an effective and complementary role for SQPF (Golding, 1998; Ganguly and Bras, 2003; Wilson et al., 2004; Sokol, 2006; Liang et al., 2010).

Each of these methods has respective strengths and weaknesses (Wilson et al., 2004). Despite NWP models' applications in weather forecasting and SQPF, they are sensitive to the initial conditions, resolution, and assimilation algorithms (Golding, 1998). With high-frequency sampling of observations from new generations of sensor networks, the ability of NWP models to provide short-term predictions is substantially improved over the US (Benjamin et al., 2004, 2009). Although there have been significant improvements in NWP models and their broad range of applications, they may still have some limitations. For example, NWP models are associated with significant computational cost, which poses limitations in terms of spatial domain, resolution, frequency, and the number of ensemble members. Extrapolation-based or "data-driven-based" algorithms, however, are capable of extracting information from the ever-increasing volume of remotely sensed data and are reported to be capable of producing reliable forecasts with respect to NWP models, especially within a few hours of the analysis time (Dixon and Wiener, 1993; Johnson et al., 1998; Germann and Zawadzki, 2002, 2004; Mueller et al., 2003; Ganguly and Bras, 2003; Chiang et al., 2006; Vila et al., 2008; Zahraei et al., 2010a, 2010b; Sokol and Pesice, 2012).

Several extrapolation-based nowcasting algorithms have been developed for hydrological applications. The Storm Cell Identification and Tracking (SCIT) algorithm and the Thunderstorm Identification, Tracking, Analysis, and Nowcasting (TITAN) algorithm are two examples (Johnson et al., 1998; Dixon and Wiener, 1993). Integration of some of these algorithms into the National Weather

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Service (NWS) Warning Decision Support System (WDSS) has been reported (Lakshmanan et al., 2009).

Pixel- and object-based are two categories of data-driven SQPF algorithms. There have been several proposed pixel-based quantitative precipitation estimation and forecasting algorithms (Grecu and Krajewski, 2000; Mecklenburg et al., 2000; Germann and Zawadzki, 2002; Montanari et al., 2006; Vant-Hull et al., 2008; Berenguer et al., 2011; Zahraei et al., 2011a, 2012). These algorithms study atmospheric phenomena from an Eulerian, pixel-based perspective. Object-based quantitative precipitation estimation and forecasting algorithms, which are the main focus of this paper, consider storm events as individual objects (Dixon and Wiener, 1993; Hong et al., 2004; Vila et al., 2008).

An object-based algorithm generally includes three steps: (1) storm identification, (2) storm tracking, and (3) storm projection. The identification and matching/tracking of each storm object at the current time (t) with the corresponding storm in the previous time step(s) (e.g., $t-1$, $t-2$, etc.) is a major challenge for nowcasting and storm life-cycle studies. Storms are dynamic in terms of intensity, texture, and geometrical characteristics. They may also split or merge with other storms, which makes the application of tracking algorithms very challenging (Machado and Laurent, 2004). Several object-based storm-tracking methods have been proposed (Lakshmanan et al., 2009), including: (1) storm-matching technique based on centroid positions (Johnson et al., 1998); (2) storm-cell matching based upon the proposed indices of overlapping pixels (Morel et al., 1997); and (3) a modified approach where storm tracking and association has been solved as an optimization problem (Dixon and Wiener, 1993).

These tracking techniques have not been without limitations. For example, the centers of mass methods are not robust in processing complex-shaped objects effectively. The overlapping technique performs well for large storm systems (e.g., Mesoscale Convective Systems, MCSs), in which storm objects are large enough to allow sufficient overlap in consecutive time steps (Lakshmanan et al., 2009; Vila et al., 2008). However, for small-scale thunderstorms, they cannot be tracked effectively using overlapping techniques. Other proposed techniques also assume that storm objects are long-lived and large enough to be associated with previous time steps (Lakshmanan et al., 2009). Although object-based algorithms are effective for SQPF, they need further improvements. As an example of newly developed object-based nowcasting algorithms, the Forecast and Tracking the evolution of Cloud Cluster (ForTraCC) has been proposed to identify, track, and forecast MCSs (Vila et al., 2008). This nowcasting tool was applied to evaluate MCS evolution up to 120 min with a 30-min interval over southern America.

In this study, a new object-based SQPF algorithm capable of tracking and forecasting storms is developed and described. The proposed algorithm, named PERCAST (PERsiann-ForeCAST), can identify and track storms from GOES-IR (infrared) cloud-top long-wave Brightness Temperature (BT) data. The term "storm" presents all atmospheric phenomena with cloud BT less than a specific threshold (e.g., 240 K) and area larger than 256 km^2. The performance of PERCAST is verified against both radar and satellite data and compared with two comparison SQPF models: (1) PERsistence (PER), and (2) WDSS-II (Warning Decision Support System-Integrated Information). The PER assumes that the future rainfall field is equal to the last available scan. The WDSS-II, developed by the National Severe Storm Laboratory (NSSL) and the University of Oklahoma, is frequently used for the identification, tracking, and nowcasting of thunderstorms (Lakshmanan et al., 2009).

The methodology of the proposed nowcasting model is presented next, followed by applied data sets, case studies, results and verification, conclusions, and appendices.

2. Methodology

The PERCAST algorithm predicts rainfall rates in the next 4 h (240 min) using infrared satellite imagery (GOES channel 10.8 μm) with time intervals of about 30 min between two consecutive satellite observations. Literature shows that a time interval of 15–30 min between two observations can be appropriately used to track storm features (Morel and Senesi, 2002; Vila et al., 2008).

There are three major steps in PERCAST, as presented in Fig. 1: (1) storm identification, (2) storm tracking, and (3) storm projection. The steps are described in detail in the following sections.

2.1. Storm identification (segmentation)

For the object-based nowcasting algorithms, effective storm segmentation is the first step. Mature convective storms can penetrate to high altitudes and, therefore, they show overshooting tops and are well associated with colder cloud BT. While BT less than 245 K can satisfactorily identify MCSs, usually the temperature between 228 K and 235 K has been proposed for the summer season, which is based on the assumption that deep convection penetrates in the upper troposphere (Machado et al., 1998; Vila et al., 2008). Vila et al. (2008) proposed a 235 K threshold for MCS nowcasting studies. The proposed PERCAST algorithm would process both mesoscale (e.g., MCS) and small-scale storm events that could not be processed through a single thresholding screening (Lakshmanan et al., 2009). It has been documented that, for cloud and precipitation studies, especially at weather scale, a single BT threshold is not robust due to seasonal, regional, and climatological variability (Adler et al., 1994; Machado et al., 1998). Even multiple threshold techniques have been reported to be problematic for severe storms (Lakshmanan et al., 2009). Therefore, a more advanced segmentation algorithm, called the watershed transform algorithm, has been applied (Roerdink and Meijster, 2001; Lakshmanan et al., 2009; Hong et al., 2004, 2005) (Appendix A).

2.2. Storm tracking and association

By defining contiguous pixels that are segmented in each storm object, matching a storm at the current time (t) with the storm's corresponding location in the previous time step(s) (e.g., $t-1$, $t-2$, etc.) is a major concern for each nowcasting model. In addition, the PERCAST algorithm needs to track both large- and small-scale events, which create more complexity.

The PERCAST model tracks storms at pixel scale, which connects pixels in two consecutive time steps through the cloud-image advection vectors (Bellerby, 2006). Further, the overlapping pixels within each segmented storm-coverage area from time t to $t-1$ are estimated. A backward-forward tracking process connects pixels in storm objects from time t to $t-1$. The contribution/tracking of a storm object from $t-1$ to another storm at time t can be calculated based on a proposed contribution function, as discussed below.

First, assume that there are two consecutive image objects at time $t-1$ and t, which correspond to the same storm/cloud, where:

- O is an object at time $t-1$, and $A(O)$ is the area of O,
- O' is an object at time t, and $A(O')$ is the area of O'.

The contribution function between O and O' (Eq. (1)) is calculated based on the number of pixels (area) being connected from the object O' at time t to O at time $t-1$ (Morel and Senesi, 2002).